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The role of human fatigue in the uncertainty of measurement

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Abstract

Risk of human error in measurement and testing is the result of the causal combination of factors and events that are involved in the process. This paper presents how to model technical and human errors and how these could interact in order to influences the reliability of measurement/test. Human errors were designed according with a System Dynamics approach with factors and states those are part of human's state and ability to handle with the process and procedures and instruments. Technical errors were related to the environment, its organization and suitability with standards. Human and Technical factors have been therefore integrated in order to predict states affecting the consistency of measure and uncertainty in range. Optimal combination of factors - based on a System Dynamics simulation and expert judgments - has been proposed according with a sampling analysis.

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1. Measurement uncertainty

Every measurement process is subject to uncertainty [1]. According to the International Vocabulary of Metrology (i.e., VIM) the measurement or test results, because of the not preventable combination of effects, does not yield to a true value. This is influenced by factors (namely "errors") systematic and random. Error is the quantified difference

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between measured and referenced quantity values. Errors contribute to "error propagation" and act on mutual causal relationship with a likelihood (probability) of occurrence for the quality of results. The upper limit of total error propagation assesses the highest accepted value of the total error usually named "uncertainty" [2]. This is generally related with accuracy and efficiency. In the Uncertainty Approach the information from measurement only permits interval of values to the measurand. Thus, the knowledge and tuning of factors/state/effects of relevant influence on error propagation can reasonably reduce uncertainty. The measurement uncertainty comes from the measuring instruments/tool, from the environment, and from the operator in terms of personal ability and bent for task, among other magnitudes of influence [3]. Procedures and process act on standards, those are the attempt to regulate the job. Humans interact with the environment - under standards and procedures - and they include factors those dynamically affect the procedure and measurement/test result. Risk of human error in measurement changes over time, mainly according to cumulative rules [4]. It is influenced by factors mitigated by procedures, training, ergonomics, recovery, concentration etc… . It needs judgments based on the severity for the quality of obtained results. In the state of art, although several studies investigated and classified according to principal shaping factors the risk of human error in measurement [5], none has investigated the effects and conditions of human fatigue and recovery, experience and knowledge, which pose important parameters to avoiding overload and gain reliability in tests. The proposal is explaining the relationships between Human Factor and Reliability of measurement under fatigued tasks in a quality assessment unit. It will provide readers with a concise overview about fatigue and recovery models. It will quantify conditions those report the growing probability of risk of error in the process of measurement.

1.1. Error Probability for uncertainty engagement

In the state of art, errors are generally distinguished according with the voluntariness of act. An error occurs whenever - because of mental and physical stress - the individual fails to achieve the intended outcome [6]. This kind of failure, as related to human, is reported inside the proposed approach under <u>Human Error Probability</u> (i.e., HEP). Human error is associated with operator error and its **Physical** and **Mental Stress** state (Fig. 2). They generally lead, under **Work Process** constraints, to systematic errors and sometimes this cannot be traced and often can create quite large errors. Operator errors identification does not mean just reading a dial or display wrong (although that happens) but can be much more complicated. Observational error, whenever humans are involved in measurement, depicts the capabilities of individual to be mentally predisposed to the measurement and may include wrong reading, wrong calculations, wrong conversion, wrong recording. Occasions when a problem is not well understood, and formal procedures and response options are not available, are under the **Mental Stress** state impact.

Otherwise, if there is not the willful disregard for the rules and procedures that govern the process (violations do not manifest), induced errors occur as technical inaccuracy. These are related to the environmental constraints, the interaction between elements in system, the misinterpretation of signals, poor choices and problem solving errors. Some are characterized as being due by the machine/instrument/tool or manufacturer, some are caused by the technologist, the measurement and testing method. A good summary of those is provided by Christopher *et al.*, 1995 [7]. The failure associated with those is included under the <u>Technical Error Probability</u> (i.e., TEP).

Into details (see Fig. 1), the validity of the measurement results is highly dependent on the technical accuracy and efficiency. This has to consider the metrological properties, and maintenance plan, of the instrument as determined by its calibration [8]. Instrumental errors are related with standards complaints. This is modelled under the state **Tool** of Fig. 1. An instrumental can be calibrated but accuracy in calibration is a costly task and sometimes this is postponed according to uncertainty range. Moreover, all instruments have a finite lifetime that is defined under the failure rate. Failures may be associated to constant in a limited time window. Maintenance plans or strategies may influence the failure rate but they work under economic portfolio. Sometimes the measurement was not placed in an optimal location for making the measurement. This is under the class of **Process** errors. Process involves procedural decision errors, or rule-based mistakes, as described by Rasmussen 1982 [9]. It occurs during highly structured tasks or procedure in the test in issue. Decisions Errors and Skill Based Errors are included under this class of **Mental Stress** state in Fig. 1. However, there are class of errors where the used device was not appropriate for the experiment. Appropriateness, that change according to the environment, is under the category of **Process** state influencing the **Environmental** error. These states include errors in calculation those are part of observations due to the environment including temperature, humidity, noise, magnetic field, vibration, wind and improper lightening.

Error Probability (*i.e.,* EP) assessment starts from the environmental design and the worker inclination toward the environment. It needs to model the operator with task. As the environment may be assumed fixed under benchmark conditions, it is the operator with the personal ability and inclination and physical effort to alter the probability of error. Thus, the proposed approach starts from operator's modeling and it arranges the uncertainty concept around the Human Reliability Assessment.

2. The human error probability

Human Factors have mostly been conceptualized as a set of rules with interactivities and collaborative capacity. Humans act in tasks including unpredictability in actions and measurand. Human factors - in the reliability analysis - are generally conceived as a source of vulnerability and uncertainty. They report actions those lead to exceeding the maximum tolerances of the conditions required for the normative work of measuring system [10]. Since 1960 have been modelling more than 90 human reliability tools in order to assess the probability of human error in specific tasks [11]. In the industrial filed, where the formulation/intervention of human reliability analysis originally starts, good practitioner and designer introduced safety factors in modelling. Those considers the probability that the human error occurs in a specific operation (it should change over time), when some causes, originated by the interaction of factors under fixed constraints, generate or could potentially originate a probability of error/failure [12]. Human affects and is affected over time by the performance requirements/conditions of production. It is required collection of data and to design about how the worker is arranged inside the system. According with the state of art about human errors probability, It is possible to distinguish between: *i)* the approaches of first generation (the oldest and somewhat simpler than ...) and *ii)* second generation (where cognitive and psychological and behavioural factors were introduced). They are mainly concentrated in the Human Reliability Analysis (HRA) as per safety and management perspectives. The former class of HRA focused on quantification of effects while overlooking factors affecting Human Reliability [13]. The latter, originated by a cognitive mapping, are mostly behavioural approaches and they were adjusted/adapted as per the environmental and productivity requirements. They assumed that users cannot be predisposed (or better "benign") in the favour of task and technology [14].

The mutual midpoint between HRA methodologies is the requirement of a human centric design. The common approach is a structured analysis to reduce the subjectiveness of the analysts and practitioner. Thus, the first step for uncertainty evaluation is to design the tasks for the measurement job. This phase is required in order to capture the dimensional benchmarks of the workstation, to report the anthropometric of humans at work, to collect test data. The results of the design phase are: the characterization of work sequence, its repetition, the allocation of a particular humanoid at work, the characterization of task in term of load exposure, time flow, measurement of the geometry of task. Constants of the processes and measurable variables are, along this phase, quantifying. The interaction between dynamic events in system remains un-resolved. Training, motivation, hardware design require definition in terms of their amount and a judgment analysis is inside required. Judgment may follow an analytical weighting process (*i.e.,* AHP) [15]. This can guarantee consistency, hierarchy in decision, sensitiveness in factors. It identifies precedence between clusters in the of HEP and TEP. Central concepts reflect perceived "influence". The possible connections are of two types: *(i)* intra-level and *(ii)* inter-level. These elements are commonly ignored in a procedural analysis but they consistently influence the quality of measurement/test.

3. The Causal Loop methodology in error assessment

Complete knowledge of errors in test and measurement requires the analysis of the system in which the task is performed, the environment where it leads, the operator – and his/her physical and psychophysical condition - and instruments that is used. Phenomena that contribute to the uncertainty are related to the fact that the result of a measurement cannot be characterised by a unique value, because of causal probability of error and thus, are called sources of uncertainty. List the possible sources of uncertainty/error are included in the schema of casual loop of Fig. 1. The steps involved are: ***STEP 1.*** DESIGN test, environment, workstation and its characteristics; ***STEP 2***. IDENTIFY and JUDGE uncertainty sources/nodes. This will include sources that contribute to the error as constant factors in the benchmark specified in Step 1, but may include other sources that act as variables that change over time under Operator and Technical assumptions; ***STEP 3***. MODEL and QUANTIFY measurable variables as dynamical components. Estimate the size of the error component associated with each potential source of uncertainty identified. Manage relations between components as per the cognitive and process engagement. It is often possible to estimate or determine a single contribution to uncertainty associated with a number of separate sources using data from validation/literature studies; ***STEP 4.*** CALCULATE causal combined error probability. The information obtained in step 2 will consist about the importance of factors. The step 3 arranges the positive or negative (or both) effects based on the overall error uncertainty assessment, whether associated with individual sources or with the combined effects of several sources. **STEP 5.** ASSESS error over time under that states. In Causal Loop Diagrams (CLD), main effects can condition the error probability of the measurement process. The CLD reports parameter as node and effects as clusters. Evaluation of probability and severity of an error scenario is possible on basis of expert judgment under ANP approach [15]. An expert in the measurement/test method - as according with Kuselmann *et al.,* 2013 [16] - judges the error scenarios, depending on tasks, in a kind of intuitive mean probability of error. We reported valuations from 5 workers and 3 ergonomists and 2 managers. Causal Loop Diagram is constructed in order to test the failure over time. This is based on a holistic vision that reports about causes of **Human** and **Technical Error Probability**. The connection between factors (*i.e.,* direct and un-direct links) is created over literature and expert revision. Weights between and across connections are elaborated across Analytic Hierarchical Approach by experts. The CLD is synthetically sketched in Fig. 1. The map requires interpretation in terms of which element contribute to …, what is the effects of that element/s. In particular, it is possible to consider different blocks in the error map:

1. Constant parameters (rhombus shape): they depend from the context, fixed as constant, and are set in DoE plan. The decision-maker can fix these as constant in order to simulate reactions.
2. Connections: these are direct (black) and indirect (grey) relationships in main states.
3. Measurable Variables (red circles): these variables act, more or less, like factors and they require continuous monitoring and controlling. They can change over time and across context (e.g., internal “temperature”, “humidity”, “lightness level”, “noise/vibration” etc ...);
4. Variables not measurable (green circles): they cannot be quantified without a design perspective. They are generally defined across tables of judgements;
5. States (yellow circles): These are the aggregate manifestation, and main clusters, of cumulative factors those are affecting the uncertainty of measurement/test across residual risk analysis.
6. Error Probability (hatched circles) as the integrated effect of Human and Technical Reliability.

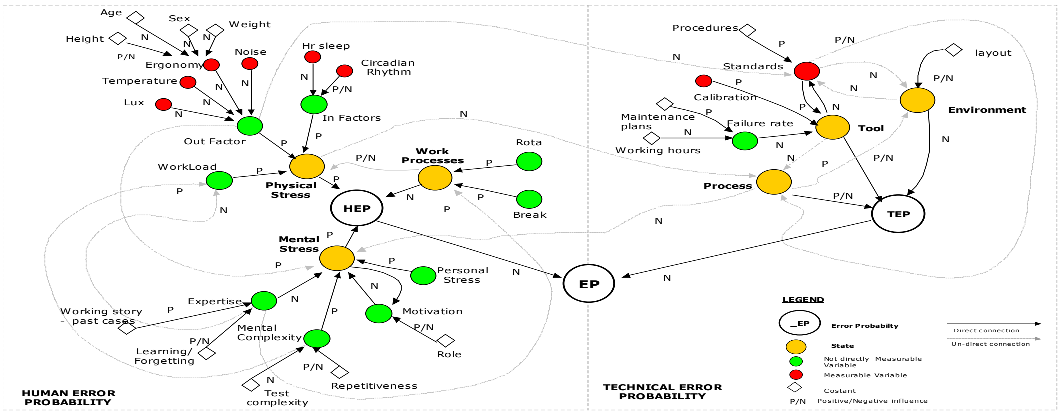

Fig. 1. Causal Loop Diagram for error manifestation in measurement/test Analysis– main relationships. Human Error Probability (i.e., HEP) and Technical Error Probability (*i.e.,* TEP) are involved in the **Error Probability** (*i.e.,* EP) analysis. P (*i.e.,* Positive) and N (*i.e.,* Negative) influence to the quality of measurement/test is indicated.

All parameters have positive (P) - the source’s growth will improve the output - or negative (N) - connection implies waste- or both (P/N) influence, in direct and un-direct connection across CLD.

Based on the contribution of different experts (10 opinions were collected by questionnaires), the proposal aims at the creation of a unique priority index for each possible decision, that summaries all expert’s judgments, minimizing their inconsistency. So, given a set of possible decisions, $G=[G_1, G_2,\dots, G_n]$, the expert has to indicate a relevance judgment of each decision compared with all the others, examined one by one. All judgments for each couple of decisions (G_k, G_j), will be synthesized using a geometrical mean through the (1).

$$j_{ki} = \sqrt[n]{j_{ki1} \cdot j_{ki2} \cdot \dots \cdot j_{kin}} \quad (1)$$

Once the resulting overall judgments are computed through equation (1), they are inserted into a square matrix (*nxn*), named comparison matrix, *C*. Consistency in *C* is required. Transitivity and symmetric properties have to be satisfied. The ranking of the possible decisions G_i, as stemming from the judgments of experts and from the field, can be computed from the entries j_{ikl} of the comparison matrix *C*. In particular, it is needed to calculate the maximum eigenvalue λ and so the relative eigenvector of all the matrix v_λ [15]. Normalizing the eigenvector (as shown in (2)), we obtain a percentage judgment, or each factor of decision, *i.e.,* for each row of the matrix *C*.

$$p_i = v\lambda \Big/ \sum_i v\lambda_i \quad (2)$$

The AHP approach intents to quantify the involvement of factors in the measurement process.

4. The role of Human Fatigue in the error assessment

Possible loss of quality because of the residual risk of human error is related to the fatigued engagement. This is about the type of task and the schedule pressure. The relation between quality of measure and fatigue may be a complex mix of effects those causally interact as operator moves between different tasks. These influence the characterization of the reference quantity values. The role of physical stress, rests break, time on work, learning and forgetting, are modelled and evaluated as factors affecting the consistency of measure and uncertainty range. Namely, for the Human Error Probability, the *In Factors* are under the direct control of the particular workforce amount in process, unlike, *Out Factors* are assumed as fixed by the process in the testing experiments. Their effect, once it is evaluated, becomes measurable in terms of standards and its acts on the environment under which the test is elaborated. Circadian Rhythm is assumed as influencing the human at work of slept privation. *Rota* and *Break* are assumed not measurable variables and fixed under strategy assignment. **Work Process** interferes with the physical stress because it mainly determines the amount of fatigue the worker reports. **Physical Stress** is mainly directly dependent by the type of task the operator is performing (*i.e., WorkLoad*), the attitude of worker to be focus on task (*i.e., In Factor*), the type of workstation and system/process conditions under assignments (*i.e., Out Factor).* The model respects the current vision: awkward posture, high force, high repetition, long durations may lead to work related musculoskeletal disorders and consequently they represent risk factors. The **Physical Stress** respects the consideration that a worker that is performing a task, maintains a Maximum Endurance Time limit (MET) [17]. MET is evaluated as fraction of the individual's maximum capability (*f*) under continuous static loading conditions

$$MET = Be^{-\beta f} \quad (3)$$

where *B* and β are static model-specific parameters. The fatigue index has been conceived as the result of the time (*MET*) x load impulse force (Maximum Load Capacity, *i.e., MLC*). The maximum Fatigue index (L_{max}) for the task *i* can be consequently statically determined

$$L_{max}^{i} = MLC \times f_i \times MET_i \quad (4)$$

Whenever in the system is going to be performed different tasks at different load conditions and under different time dependent state, the amount of physical stress the worker is storing up can be defined as L_T after time *T*

$$L_T = \sum f_i t_i - a_i b_i \quad (5)$$

Where t_i is the length (of time) of task *i*, b_i is the break time following task *i* (in cycle *j*) and a_i is the allowance rate defined in

$$a_i = \frac{L_{max}}{RA_i \times MET_i} \tag{6}$$

With RA_i (Rest Allowance) required for task i as fraction of MET_i [18]. In the equation (5), task time t_i is required. Time depends from the workload. It is un-directly connected with training and mental complexity. The more are the times (k - repetitions) the worker is performing the task i, the lower is cycle time.

$$t_{ik} = T_{i1} k^{-l} \tag{7}$$

Where t_{ik} is the time required for the i task after k repetitions and l is the learning rate worker report. This means: it is needed a monitoring and controlling step where repetitiveness can be assumed as constant (assigned at the work day). Starting from learning, after $m \geq k$ repetitions workers reacts with forgetting rate f.

$$t_{im} = T_1 m^f \tag{8}$$

Forgetting is a worker related effect. It could depend from mental attitude and task complexity. It is will act improving fatigue and, consequently, boosting failure rate in its **Physical Stress** state.

The amount of MET_i and MLC depends from the "ergonomy" in design. Ergonomics is modelled according to standards [19]. **Work Process**, **Physical Stress** and **Mental Stress** determine, as state in CLD, the numerousness of repetition the system may guarantee. Effects of fatigue in quality measurements teste are hereafter analysed.

5. Results and discussion

The findings are tested with collaboration of real tests problems in a quality division unit. The model considers that workers alternate between tasks for m cycles over T= 480 min. The worker has to check the quality of product according to dimensional control, roughness and burr measurement, minor and inside diameter, depth in features. The tasks are separated according with the class of product that are of different materials and dimension. Products are classified according to groups of similar dimension and complexity from $D1$ to $D5$ (Table 1). The worker has to spend a minimum time (e.g., t_{min} = 2,55 min) worker for each task before being transfer to another job. The operator will be required to work a fraction of maxim load capacity (MLC). In Fig. 4 different MVC - means type of tasks - are implemented and the corresponding Error Probability is reported. Different lengths of break are evaluated. We starting from assuming that the job is constituted by m tasks on $D5$ dimensional products and that the length of break between tasks is not enough to result in the full recovery according to RA (Fig. 3 a and b). About m= 11 repetitions of tasks are allowed in T. As described in Fig. 2. (a) fatigue builds over the duration of shift. Fig. 2. (b) reports the possible Error Probability assuming that the Technical Error Probability of CLD works as constant between **Environment** and **Tool** and **Process** state. The condition of errors has been related to a failure rate and simulated - according to a System Dynamic (SD) approach during the shift. SD reported the outcome of non-measurable effects [20]. For the experiments as per Fig. 2, 3, 4, 5 and Table 2 it was investigated the prioritization index for each factor that influence the error measurement as per the opinion of the experts and the workers directly involved in the five jobs. In the case of Human Error Probability, the prioritization list is reported as follow: Ergonomics = 17,40%; Expertise = 13,20%; Task/Procedural Complexity = 13,20%; Repetitiveness in Task = 12,60%; Rota-Breaks = 9,70% Weight = 9,20%; Responsibility = 8,20%; Age = 7,60%; Noise = 7,50%; Others = 1.4%. In case of Technical Error Probability it has assumed a measurement process of different difficulties according to the duration of Task and type of work.

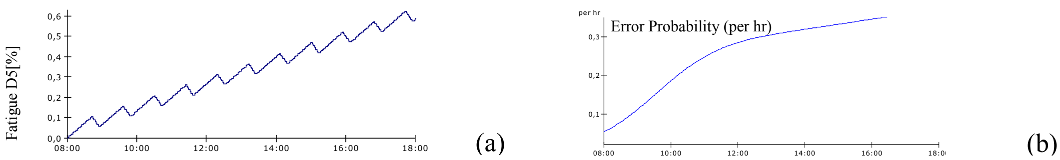

Fig. 2. Schematic fatigue with work rest schema (a) and Error Probability (b) over time T for m= 11 repetitive tasks - class D5 - with no full recovery break (RA= 50%, MVC= 0,5) and Constant Technical Errors state (weighted of each state 0,1).

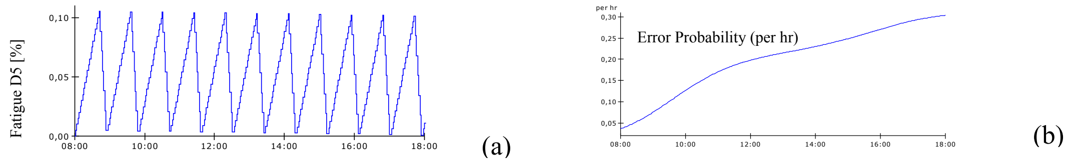

Fig. 3. Schematic fatigue with work rest schema (a) and Error Probability (b) - class D5 - over time T for m=11 repetitive tasks with full recovery break (RA= 100%, MVC= 0,5) and constant Technical Errors state (Weighted state = 0,1).

The instrument has a regular working history with constant maintenance plans. The environment is configured in order to test situations without systematics in error. The relative importance of **Process** and **Tool** and **Environment** is set at 0,2 each. This concludes, as per the CLD map, a constant Technical Error Probability of 0,15 in average.

The failure rate is then been connected with a reliability index- $RA = e^{-\int_0^T \lambda(t)dt}$. In table 2 there is the results of the CLD for different hours in work and for the five jobs as per Table 1. Tasks with more complexity generates lower reliability and higher probability of error. The amount of repetition m may alter (Table 2) the failure rate.

Under constant **Tool** and **Process** and **Environmental** states the fatigued tasks report higher Probability of Error with instability in the fatigue cumulative effort (Fig. 5 (a) and (b)). The higher is physical effort, the lower is the reliability under fixed rest break. The lower is the rest, the higher is the fatigue over the same process requirements (m replications) (Fig. 2 and 3).

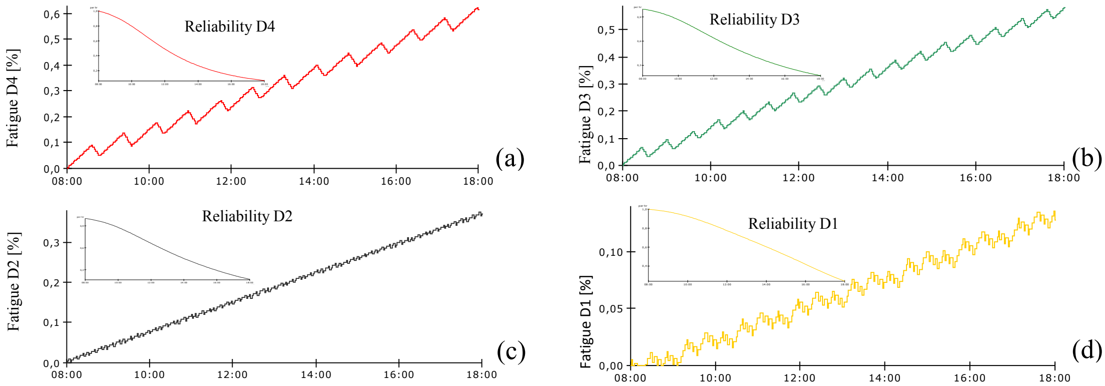

Fig. 4 Schematic fatigue with work rest schema over time *T* for *m* repetitive tasks – class: D4 **(a)**; D3 **(b)**; D2 **(c)**; D1 **(d)** - with no full recovery break (*RA*= 50%, *MVC*=0,5). Upper left corner is reporting the Reliability under Fixed (0,2) Techcnical constraints (min value of: 0.18 (a); 0.26 (b); 0.28 (c); (0.32 (d)).

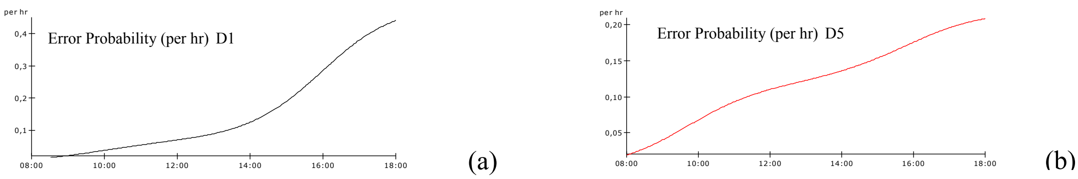

Fig.5. Error probability over 8 working hours under *m* tasks of class D1 with MVC = 0.6 **(a)** and D5 with MVC = 0.1 **(b)** (short task time) and partial recovery (RA= 0,5) – Constant Technical Error (0,13).

Table 1: Task characteristic in the process under investigation.

	Task D1	Task D2	Task D3	Task D4	Task D5
Mean n.ro of features to check	6	17	22	30	50
Mean Time –for Quality Check [min]	2,55	5,76	33,25	45,46	52,26
Rest allowance [%]	50	50	50	50	50
Percentage of MLC [%]	10	10	10	10	10
Repetition allowance in 8 hours	180	120	0,18	13	11

6. Conclusions

A method for the quantification of human error in uncertainty of job is proposed. The intent is to include characterization of conditions that are generally ignored by standards but those could consistently affect the uncertainty in outcomes. Fatigue and recovery aspects influence the way by which sequence of tasks has to be defined. Operator acts on the quality of measurement according to anthropometrics, experience, attitude for work, maximum endurance and fatigue capability. The job reflects its complexity, load level, alternation between tasks, repetitions. Human error probability is generally lower in tasks with longer recovery, shorter and interrupting procedures. Simple tasks with heavy effort reports higher probability of error than complex and longer tasks with light weight. These conclude longer schedule with a time dependent relevant effect of fatigue in uncertainty of measure. Complex measurement tasks are associated with continuous breaks and shorter recovery rate. These include lower risk of error but growing forgetting attitude in procedures.

Table 2: Failure rates for job in class D1, ..., D5 executed in the work shift time span.

Time	$\lambda_1 (t)*\Delta t*10^{-3}$	$\lambda_2 (t)*\Delta t*10^{-3}$	$\lambda_3 (t)*\Delta t*10^{-3}$	$\lambda_4 (t)*\Delta t*10^{-3}$	$\lambda_5 (t)*\Delta t*10^{-3}$
8:00	0.01	0.03	2.00	3.00	4.20
8:30	3.00	3.00	3.20	7.56	8.50
9:00	7.40	5.01	4.50	12.58	11.21
9:30	7.50	7.20	6.20	13.26	13.87
10:00	8.00	12.15	11.58	18.20	18.50
10:30	10.53	12.60	16.20	20.12	19.20
11:00	11.00	14.20	17.20	24.29	23.50
11:30	12.15	15.20	18.45	26.50	25.61
12:00	13.00	18.15	18.55	29.02	28.50
12:30	13.05	18.40	19.05	29.50	29.52
13:00	13.10	18.50	19.22	29.80	29.89
13:30	13.30	19.55	19.38	30.12	30.12
14:00	16.00	20.00	20.02	30.28	31.56
14:30	16.30	20.12	20.16	30.58	32.22
15:00	18.05	20.59	20.18	31.60	32.80
15:30	22.10	21.30	20.23	31.83	33.15
16:00	22.20	22.20	20.56	32.20	33.45
16:30	24.13	24.00	20.60	33.40	34.58
17:00	28.15	26.80	20.80	34.50	36.49
17:30	31.20	27.50	21.80	36.20	37.60
18:00	32.40	28.30	22.14	36.50	38.50

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